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Hybrid Emotion-aware Monitoring System based on Brainwaves for Internet of Medical Things

Weizhi Meng, *Senior Member, IEEE*, Yong Cai, Laurence T. Yang *Fellow Member, IEEE*, and Wei-Yang Chiu

***Abstract*—Driven by an increasing number of connected medical devices, Internet of Medical Things (IoMT), as an application of Internet of Things (IoT) in healthcare, is developed to help collect, analyze and transmit medical data. During the outbreak of pandemic like COVID-19, IoMT can be useful to monitor the status of patients and detect main symptoms remotely, by using various smart sensors. However, due to the lack of emotional care in current IoMT, it is still a challenge to reach an efficient medical process. Especially under COVID-19, there is a need to monitor emotion status among particular people like elderly. In this work, we propose an emotion-aware healthcare monitoring system in IoMT, based on brainwaves. With the fast development of EEG (electroencephalography) sensors in current headsets and some devices, brainwave-based emotion detection becomes feasible. The IoMT devices are used to capture the brainwaves of a patient in a scenario of smart home. Also, our system involves the analysis of touch behavior as the second layer to enhance the brainwave-based emotion recognition. In the user study with 60 participants, the results indicate the viability and effectiveness of our approach in detecting emotion like comfortable and uncomfortable, which can complement existing emotion-aware healthcare applications and mechanisms.**

***Index Terms*—Brainwave, Emotion-aware applications, Touch behavior, EEG signal, Heathcare and IoMT.**

I. Introduction

INTERNET of Things (IoT) currently maintains a growing trend, which enables thousands of devices connected with each other and exchange information via Internet [45]. The Gartner study [20] estimated that the market of enterprise and automotive IoT will reach 5.8 billion endpoints by the end of 2020. In addition, the Deloitte report echoed that more than 310 billion dollar had been invested by industry in order to develop IoT technology in various disciplines [11].

The Internet of Medical Things (IoMT) is an application of IoT technology in the heathcare domain. It is a consolidation of medical devices and software that can connect with heathcare systems and people and facilitate the exchange of medical information using wireless communication technologies [3]. In other words, IoMT provides an infrastructure of healthcare applications, systems, services and medical devices. According to a study from Deloitte, the market of IoMT was estimated to be worth around $158 billion by the end of 2022 [12]. The major advantage of IoMT is to allow monitoring patients' status remotely and providing more accurate diagnoses. Further, IoMT is expected to save around $300 billion annually in the healthcare industry [21].

For instance, smartphones are considered as one main IoT device to assist medical professionals for their medical tasks. Due to the portable intelligence, smartphones can help maintain the communication in real-time and exchange required medical data. With the increasing importance and popularity, a set of smartphones can form a special IoMT environment - Medical Smartphone Network (MSN) [30], which can improve the efficiency and effectiveness of performing medical operations. The smartphone can act as a gateway to collect data and perform the desired processing tasks like filtration and feature extraction [35].

Currently, the outbreak and spread of COVID-19 may accelerate the requirement for IoMT devices to quick monitor and examine patient symptoms. Under the global pandemic, there is a need to develop personal emergency response systems for people, especially for children, elderly, and mental disorder people, who may need emergency assistance [21]. The IoMT devices like smart diagnostic devices and tracking wearables can significantly reduce the need of face-to-face diagnosis and increase the quality of patient care.

Motivation. In the literature, many smart IoMT approaches and mechanisms have been proposed, which can make decisions intelligently and take actions automatically [3]. While emotion-aware abilities are often not integrated with current IoMT solutions. Recent research [36] has highlighted that people may suffer negative emotions under COVID-19 such as anxiety, depression and schizophrenia. Hence there is need to integrate emotion-aware abilities into IoMT applications, with the aim of providing patients with personalized therapy recommendations. For example, Hossain and Muhammad [22] introduced an emotion-aware healthcare framework based on 5G and big data analysis. They built an emotion recognition system by considering the features extracted from speech and image signals. A decision could be made by fusing the scores from both signals.

Contributions. With the rapid advancement in bio-sensor technologies, brainwave recognition based on EEG (electroencephalography) signals becomes feasible and popular in recent years. Brainwave as a kind of complicated signal of the active brain can represent the action and intent from people. To the best of our knowledge, emotion recognition based on branwaves has not been widely studied in the healthcare domain. With more wearable healthcare devices like headsets

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being available in the market, we believe that brainwaves can complement existing emotion recognition and offer a more efficient medical process. Motivated by this trend, we propose an emotion-aware healthcare monitoring system in IoMT, with a brainwave-enabled structure. Our contributions can be summarized as follows:

- We propose a brainwave-based emotion-aware healthcare monitoring system that can complement existing emotion-aware IoMT applications and mechanisms. In our system, we consider a two-layer structure, where the first layer can recognize emotions based on brainwaves to identify comfortable and uncomfortable effects, and the second layer can confirm the emergency scenario via the analysis of behavior patterns like touch behavior.
- To analyze brainwave and classify emotions, we introduce a hybrid classifier of Feed-Forward Neural Network with First-Order Stochastic Optimization algorithm, named ADAM. The ADAM algorithm is used to update the weight matrices and minimize the loss function of Feed-Forward Neural Network.
- In the evaluation, we setup an environment for collecting data and perform a user study with a total of 60 participants. Our experimental results demonstrate the viability and effectiveness of our proposed system in recognizing people's emotion and can be extended as a personal emergency monitor system.

The remaining parts of this work are organized as follows. In Section II, we introduce the background on brainwaves, and present related work on brainwave-based authentication and emotion recognition. Section III details our proposed emotion-aware monitoring system and the hybrid classifier. Section IV describes our user study and analyzes the results. Section V discusses the limitations and open challenges, and Section VI concludes our work.

II. Background and Related Work

This section first introduces brainwave signals and then review relevant studies on brainwave-based authentication and emotion recognition.

A. Brainwave and Collection

The brain is believed to be a complicated system, which consists of roughly 100 billion nerve cells known as neurons. The mental states can spark from the interactions between functional and physical layers. The neurons in the brain are responsible for collecting and transmitting electrochemical signals, simply brainwaves [14]. In practical usage, how to collect brainwave signals through EEG sensors is the fundamental issue of all brainwave-based authentication schemes. Based on the method on how to capture the brainwave signals, we can have two categories as below:

- The invasive brainwaves: such brainwave signals are captured by external devices like camera. It can provide the best quality signals, but may suffer from scar-tissue and weak signal problems.
- The non-invasive brainwaves: such brainwave signals are captured by the surface of the skull, i.e., changes in EEG state. Its quality is not the best, but is the safest and the most convenient way to record EEG.

The invasive brainwaves usually require installing brainwave sensors under skins, which attempt to provide a better reading as compared with non-invasive brainwaves. However, the inconvenience of mounting and unmounting makes the invasive brainwave sensors comparatively impractical for common authentication. In current market, most commercial brainwave sensors are non-invasive, which are easy to mount and operate. Most of them are headset-like devices that users can easily use and mount like brainwave-sensing headset - Neurosky [33] and meditation made headband - Muse [34]. Since brainwaves can display one's intents and feels, there is an increasing growth of brain-computer interface (BCI) applications by utilizing various sensors like headsets.

B. Advantages of using Brainwaves

As compared with other popular commercial biometric authentication schemes like face recognition and fingerprint, brainwave as an authentication token can provide the complexity and the uniqueness among individuals, as well as easy usage and flexibility of change. It is also believed that brainwaves are difficult to copy and replay [4]. For example, it is known that both face and fingerprint cannot be revoked or cancelled, but brainwaves can be revoked and changed according to the custom tasks, i.e., various custom tasks can trigger different reactions [40]. Also, using brainwave signals (EEG) can benefit building smart environments like smart city, where a user is feasible to control home appliances without physical touches.

In addition, a system using brainwaves as authentication token does not require any physical interaction between the human and the computer. This is an important characteristic and advantage of brainwave-based authentication. For traditional password-based system, a user performing any explicit operations to the system (such as inputting a password) can give a chance for attackers to intercept or intimidate these credentials. By contrast, using brainwave-based authentication does not require the user to do any explicit interactions with the system, which can greatly increase the hacking difficulty for attackers. Further, brainwaves can provide more combination possibilities and larger password space. For a typical US keyboard, there are 95 printable characters, and for a k-word long password, the combination is H_k^{95}. While for a brainwave-based system, the possible combinations are H_e^r, where r means all the possible reactions of brainwave (much greater than 95), and e is the number of custom tasks for authentication.

Similar to behavioral biometrics such as keystroke dynamics [32] and touch dynamics [31], brainwaves can also be used for continuous authentication. For example, brainwave sensors can be embedded into wearable devices and verify the brainwave signals in a continuous way. If a significant deviation is identified, the system can react according to the pre-defined security policies. By contrast, traditional textual passwords & tokens and most physiological bimetrics (e.g., face, fingerprint) can mainly provide a one-time verification

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to decide whether a user can access the system, but cannot protect the system after a successful login.

C. Brainwave-based Authentication

The same as other biometric authentication schemes (e.g., face, touch dynamics), machine learning is also the most widely used tool in brainwave-based authentication. Table I depicts some relevant studies on brainwave-based authentication. Many learning classifiers have been investigated.

TABLE I
RESEARCH OF BRAINWAVE USAGE ON AUTHENTICATION AND IDENTIFICATION

Work	Attribute		
	Auth. By	**Classifier**	**Accu.**
[18]	Reactions towards visuals	FRNN	90.17%
[19]	Reactions towards environmental sound and visual recognition	FRNN with refinements	96.40%
[27]	Reactions towards imagination movements and words consideration	GMM/MAP	92.90%
[38]	Reactions towards the motor imagery of hand, foot, and tongue	SVM	96.10%
[9]	Reactions towards visuals	SVM	100%
[40]	Reactions towards visuals	SVM	90.04%

Linear classifiers, such as LDA, QDA and SVM, can use the value of linear combination of the data characteristics to achieve the goal of statistical classification. However, the more dimensions a set of data has, the more complex the calculation may become. Table I shows that SVM is one of most popular classifiers for brainwave-based authentication [38], [9], [40].

Nearest Neighbor classifiers like kNN and FRNN adopt the idea that the same class of data should be closer in the feature space to achieve data classification. Taking kNN as an example, by given a query point, it determines the class of the query point of calculating the distance among the k data points that are closest to the query point, where k is a constant determined by the user [39]. The simplicity makes it a popular baseline algorithm [18], [19].

Neural Network classifiers like Probabilistic Neural Network [7] present a collection of artificial neurons arranged in multiple layers with multiple connections between nodes. Each node can receive and process the signals from their previous node, and then should decide and output the result to the selected node in the next layer. The main advantage of neural network is the ability to help solve any non-linear decision problems.

Table I shows that FRNN and SVM are widely adopted for brainwave-based authentication, whereas Lotte et al. [23] figured out that many classifiers like FRNN, SVM, Probabilistic Neural Network could be used for measuring stimulation and reaction, while are not suitable for classifying all brainwave signals. That is, the classifier performance is fluctuant based on the specific data. To mitigate this issue, a hybrid classifier could be a solution. In this work, we propose a hybrid classifier (FFNN+ADAM) by combining Feed-Forward Neural Network with First-Order Stochastic Optimization algorithm (ADAM). The use of ADAM can maintain the performance of FFNN.

Liew et al. [25] introduced an Incremental FuzzyNearest Neighbour (IncFRNN) technique for EEG authentication using feature extracted visual evoked, which could reduce the required training data during model initialisation. As compared with the incremental K-Nearest Neighbour (KNN) technique, IncFRNN was found to be statistically better. Moctezuma and Molinas [28] focused on EEG identity authentication and used 56 channels from event-related potentials (ERPs) for subject identification. The ERPs are extracted from positive or negative feedback-related responses of a P300-speller system. The evaluation with SVM classifier showed that an accuracy of 0.93 could be achieved with a male-only population. Zhang et al. [44] introduced DeepKey, a multimodal biometric authentication system, which combines EEG and gait signals to defend against intruders. The system is mainly composed of an Invalid ID Filter Model and an identification model. The former aims to reduce unauthorized access requests while the latter aims to identify both EEG and gait signals using Recurrent Neural Network (RNN). Some more related research studies can refer to a recent survey [6].

D. Emotion Recognition

Emotion recognition has been widely studied in the research community, with the aim of identifying human emotion via the analysis of speech, image, or video. Chen et al. [8] presented a method of emotion recognition based on speech by using a two-layer fuzzy multiple random forest (TLFMRF). To consider the difference in people, they fused the features from both personalized and non-personalized data. TLFMRF could achieve an accuracy rate of 85.80% of happy and 98.60% of sad. Zhang et al. [42] applied deep learning for emotion recognition based on image content. By integrating the style and content presentation, their deep convolutional neural networks could reach 71.77% accuracy on the image emotion dataset, which was better than most other similar approaches.

Zhang et al. [41] introduced an approach of identifying emotions by extracting some physical elements of a video like sound and color. The multilayer perceptron (MLP) classifier could provide an accuracy rate of 95% under their experimental settings. More related work can refer to several survey studies [1], [13], [43].

In recent years, research also considers brainwaves in emotion recognition. Kim and Kang [17] utilized brainwaves to examine users' emotion like joy, fear and sadness, when using smartphones. Beck et al. [5] studied the emotion recognition based on high quality EEG recordings, by extracting 7 different features. With the recording from 40 participants, the classifier of artificial neural network could provide an accuracy range from 70% to 75%. Some survey work on EEG-based emotion recognition can refer to [2], [37].

To the best of our knowledge, brainwave-based emotion recognition has not been widely studied in healthcare, this motivates our work to develop an emotion-aware monitoring system to provide better personalized therapy recommendations by considering the effects of brainwaves.

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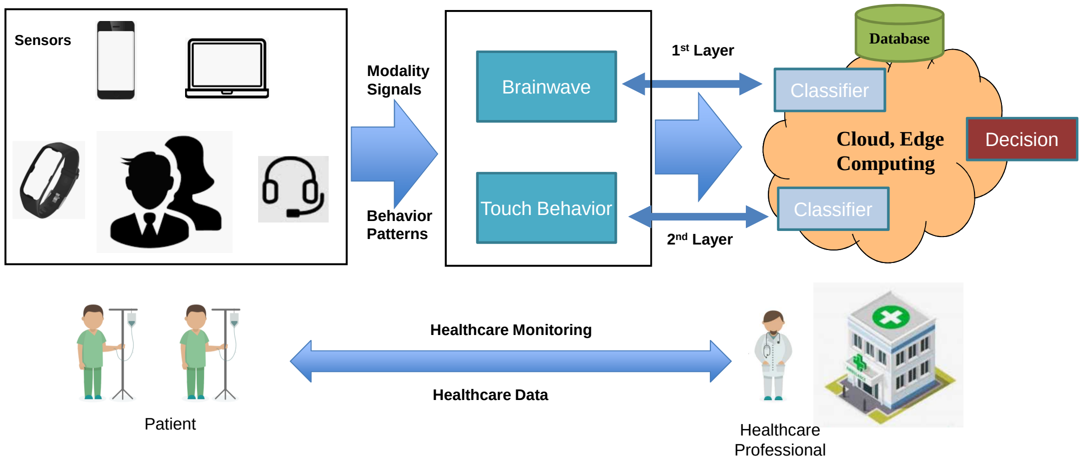

Fig. 1. The architecture of our emotion-aware healthcare monitoring system.

III. Our System

In this section, we introduce our emotion-aware healthcare monitoring system and the devised hybrid classifier of Feed-Forward Neural Network with ADAM.

A. System Architecture

During the global pandemic of COVID-19, there is a need to consider people's emotion for an efficient medical process. Emotion recognition is helpful to judge whether people are facing emergent scenarios, especially for children, elderly and mental disorders. Fig. 1 depicts the architecture of our proposed emotion-aware healthcare monitoring system, which adopts a two-layer structure by collecting brainwave signals and behavior patterns.

Modality data. The first layer in our system is to collect brainwave (or EEG) signals. Intuitively, when users face some pains or emergent scenarios, they will have negative feelings like unpleasant, arduous or painful. The generated brainwave signals would be different from the normal conditions, which can help healthcare professionals to detect some anomalies timely. Our system can also integrate other modality data like speech and image, which can collaborate with existing emotion-aware solutions like 5G-enabled emotion-aware healthcare big data framework [22].

Behavior data. The second layer in our system aims to collect behavior patterns. When people are painful, there could be a great deviation in their behavior and actions. As touchscreen-enabled smartphones are a major IoMT device (e.g., [24], [31]), our system considers touch behavior in confirming the patient's situation. This layer can complement the output from the first layer, as brainwave-based emotion recognition is not stable and could be easily affected [2], [37]. Hence the two-layer structure can help reduce the false alarms proposed by our system.

The two-layer monitoring system can provide some advantages when deployed in a practical environment.

- *Flexibility.* With many wearable sensors available in the market, e.g., a smart home environment, various modality and behavior data can be collected. Our system can be configured according to the concrete requirements from a patient and a healthcare organization.
- *Extensibility.* Thanks to the layer-based architecture, our system is easy to be extended by involving other sensors. In addition, more layers can be implemented without the modification of other layers.
- *Computation.* Similar to existing emotion-aware applications and mechanisms, our system can utilize a cloud and edge computing environment, with the purpose of reducing the computational burden locally. For example, the data can be collected and analyzed by a privacy cloud controlled by the healthcare organization.

The main purpose of our system is to complement existing emotion-aware IoMT solutions, where our system can easily collaborate with current systems and mechanisms to provide a multimodal recognition of human emotion.

B. FFNN with ADAM

To recognize emotions based on brainwaves, we devise a hybrid classifier of Feed-Forward Neural Network with First-Order Stochastic Optimization algorithm called ADAM.

A Feed-Forward Neural Network (FFNN) usually consists of an input layer, k hidden layers, and an output layer can be seen as a $(k+2)$-partite graph. Let the input layer be given by an input vector $x = (x_1, x_2, ..., x_{n-1}, 1)$ with dimension $(1, n)$, where each element x_i for $i \in \{1, ..., n-1\}$ in the vector corresponds to a sample feature. The constant 1 is added to include a bias term.

Let $W^{(l)}$ denote a *weight matrix* of dimension $(m \times n)$ corresponding to the transformation between layer $(l-1)$ and l. It can be seen as a mapping $M^{(l)} : R^n \rightarrow R^m$ in which n is the number of entries in the input vector x, and m is the number of entries in the output vector y. Let the specific mapping be given by $M^{(l)}(x) = W^{(l)} \cdot x^T = y$.

A Feed-Forward Neural Network consists of stacking multiple layers together. Introducing the concept of an *activation function* will allow the network to mimic highly

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non-linear functions. Let a non-linear activation function be denoted by ϕ and let $z = \phi(y)$ where ϕ is applied to each entry of the vector y.

Combining the concepts introduced so far leads to the following definitions of each entry:

$$y_i^{(l)} = (M^{(l)}(x))_i = (W^{(l)} \cdot x^T)_i = \sum_{j=1}^{n} x_j \cdot w_{i,j}^l$$
$$z_i^{(l)} = \phi(M^{(l)}(x))_i = \phi(W^{(l)} \cdot x^T)_i = \phi(\sum_{j=1}^{n} x_j \cdot w_{i,j}^l)$$

To demonstrate let a Feed-Forward Neural Network consist of an input layer, two hidden layers, and an output layer. In the output layer $l = 3$, which corresponds to the vector $z^{(3)}$.

$$z^{(3)} = \phi(M^{(3)}(\phi(M^{(2)}(\phi(M^{(1)}(x))))))$$

The composite function is named the *hypothesis*, and it is usually denoted by $h_\Theta(x)$. Here Θ refers to all the weight matrices $W^{(l)}$.

In order to train the weight of FFNN, there is a need to quantify the error made in the classification. This can be achieved by using a cost function, which is essentially an average of the losses associated with each prediction. With such a function, our goal is to minimise the below.

$$_\Theta J(\Theta) = \frac{1}{m} \sum_{i=1}^{m} L_i(h_\Theta(x)_i, y_i)$$

The loss function L is of high importance to the quality of trained classifier. The loss function is critical to handle non-convexity of the space, which in turn ensures non-ambiguity with regards to the optimal local minimum. Also, the function decides how fast convergence towards optimum. This work employs one of the most commonly used loss functions - *log loss* [15].

$$L(h_\Theta(x)_i, y_i) = -\sum_j [y_j \log p(o_j)]$$

In the above y_j refers to the j'th element of true class labels encoded using one-hot-encoding. For the predicted labels o_j refers to the $j'th$ element.

To update the weight matrices and minimize the loss function of Feed-Forward Neural Network, we can use gradient a number of training examples to approximate the gradient is known as the *batch size*. Let Θ denote a vector of weight matrices $W^{(l)}$. We use ADAM [16], an algorithm for first-order gradient-based optimization to achieve this, as described in Algorithm 1.

Algorithm 1: ADAM

Require: α: Stepsize
Require: ϵ: Small number to avoid division by zero
Require: $\beta_1, \beta_2 \in [0, 1)$: Exponential decay rates for the moment estimates
Require: $f(\Theta)$: Stochastic objective function with weight matrices Θ
Require: Θ_0: Initial weight matrices.
$m_0 \leftarrow 0$ (Initialise first moment vector)
$v_0 \leftarrow 0$ (Initialise second moment vector)
$t \leftarrow 0$ (Initialise timestep)
while Θ_t not converged **do**
  $t \leftarrow t + 1$
  $g_t \leftarrow \nabla_\Theta f_t(\Theta_{t-1})$
  $m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$
  $v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$
  $\hat{m_t} \leftarrow m_t/(1 - \beta_1^t)$
  $\hat{v_t} \leftarrow v_t/(1 - \beta_2^t)$
  $\Theta_t \leftarrow \Theta_{t-1} - \alpha \cdot \hat{m}_t/(\sqrt{\hat{v_t}} + \epsilon)$
end while
return Θ_t

The parameter t denotes the iteration number, indicating how many times the while-loop has been executed. The gradient $\nabla_\Theta f_t(\Theta_{t-1})$ is the matrix of partial derivatives corresponding to the weight matrix Θ. The first moment vector m_t is the expected value of the gradient at iteration t, and the second moment vector v_t is the expected value of the gradient element-wise squared. It can be shown by expanding the recursive formula [16]. After the expansion we can have the following:

$$m_t = E[g_t] \cdot (1 - \beta_1^t) + \psi$$
$$v_t = E[g_t^2] \cdot (1 - \beta_2^t) + \psi$$

We then have the following by inserting the new expression into $\hat{m}_t$ and $\hat{v}_t$ respectively.

$$\hat{m}_t = \frac{E[g_t]\cdot(1-\beta_1^t)+\psi}{(1-\beta_1^t)} \approx E[g_t]$$
$$\hat{v}_t = \frac{E[g_t^2]\cdot(1-\beta_2^t)+\psi}{(1-\beta_2^t)} \approx E[g_t^2]$$

Based on the above terms, we can know how to interpret the updates as below.

$$\Theta_t \leftarrow \Theta_{t-1} - \alpha \cdot \hat{m}_t/(\sqrt{\hat{v}_t} + \epsilon) \approx \Theta_{t-1} - \alpha \cdot E[g_t]/(\sqrt{E[g_t^2]} + \epsilon)$$

When the ratio between the uncentered variance $E[g_t^2]$ and the mean $E[g_t]$ becomes large, we can have a better confidence in the update direction. Based on the work [16], we adopted the default settings $\epsilon = 10^{-8}, \beta_1 = 0.9, \beta_2 = 0.999$, and $\alpha = 0.001$.

IV. Evaluation

This section introduces our user study with experimental settings, and analyzes the collected data.

A. User Study

As most current datasets do not fit our scenario, in order to investigate the viability and performance of our system, we conduct an approved user study with 60 participants, who were recruited via Emails and colleague recommendation. We also collaborated with a healthcare organization to provide advice on our procedure. Table II summarizes the information of participants including age and occupation.

TABLE II
PARTICIPANTS INFORMATION IN THE STUDY.

Age	Male	Female	Occupation	Male	Female
Age 20-30	24	25	Students	20	23
Age 31-45	5	6	Researcher&Staff	9	8

TABLE III
ENVIRONMENT CONFIGURATION

Hardware Software	**Attributes**	
	Specification	**Description**
Notebook	Thinkpad T495	Displaying videos to the participants
Desktop	ThinkPad T14s Gen 1	Collect and analyze data
Brainwave Headset	Muse 2 [34]	A multi-sensor meditation device that provides real-time feedback on brain activities
Program Platform	Oracle Java 11	The platform is responsible for displaying videos and sending data for analysis
Brainwave Collector	Muse 2 APK	The program extracts the Brainwave headset's signal and the data from the custom program

To better simulate the emotions of participants with either comfortable or uncomfortable, we performed a pre-interview with each participant and collected some movie clips (around 30 seconds each) based on their feedback. During the study, participants have to wear the Muse headset, which can capture their brainwave signals, when they watch the video clips. We also provided an Android phone (Samsung Galaxy Note) to require them inputting the given unlock patterns and collect their touch behavior. Table III depicts the environmental setup including the laptop and the headset.

In order to capture good-quality EEG signals without being affected by video playing, we use the following steps to show clips, based on the previous studies [40].

- A 15-second blank screen to attract participants and make them calm down.
- After playing a clip, each participant requires to input three unlock patterns on the provided Android phones. Return to the above step.

To avoid the possible influence caused by the screen display, we collected the brainwave signals by playing the video in the fullscreen mode. Also, we provided the same guideline to each participant.

B. Study Result

To compare the performance, we involve some typical and popular supervised classifiers such as J48, NBayes, SVM and BPNN. These classifiers were extracted from WEKA platform (https://www.cs.waikato.ac.nz/ml/weka/), which is a collection of algorithms. We used 70% of the collected data for training and the rest for testing. Algorithm 2 shows the K-fold cross validation and this work used ten-fold cross validation (where $K = 10$).

Algorithm 2: K-fold Cross Validation

Let X be the training data consisting of n samples
Let x_i where $i \in \{1,..,k\}$ be $\frac{n}{k}$ samples from X such that $x_i \cap x_j =$ for $i \neq j$.
Let $s = 0$
for $j = 1$ to k **do**
  Train the model on x_i for $i \in \{1,..,k\}/j$.
  Compute performance metric PM_j on unseen x_j.
  $s = s + PM_j$
end for
Return $\frac{s}{k}$

For evaluation metrics, we have true positive (TP), true negative (TN), false positive (FP) and false negative (FN). Hence we can derive the accuracy and hit rate as below:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Hit rate} = \frac{TP}{TP+FN}$$

Fig. 2 shows the classification accuracy and hit rate regarding different classifiers. It is found that our devised hybrid classifier could achieve better accuracy rate and hit rate (85.7% and 88.4%) than other classifiers (SVM: 81.4% and 84.4%; J48: 75.5% and 76.7%; NBayes: 74.2% and 78.4%; BPNN: 79.4% and 82.9%). Also, it showed that the hybrid classifier could outperform FFNN, this is because the hybrid classifier can use the ADAM algorithm to help update the weight and minimize the loss function.

To further explore the performance of FFNN-ADAM, Fig. 3 shows the achieved accuracy for each participant. It is visible that the accuracy varied with each participant. For example, the accuracy could be close to 90% for some participants with number 6, 14, 18, 22, 26, 30, 36, 49, 56 and 58. While the accuracy was low to around 67% for participants with number 16, 31, 50 and 59. The main reason is that the EEG signals may be not the same (and stable) for each participant, even though

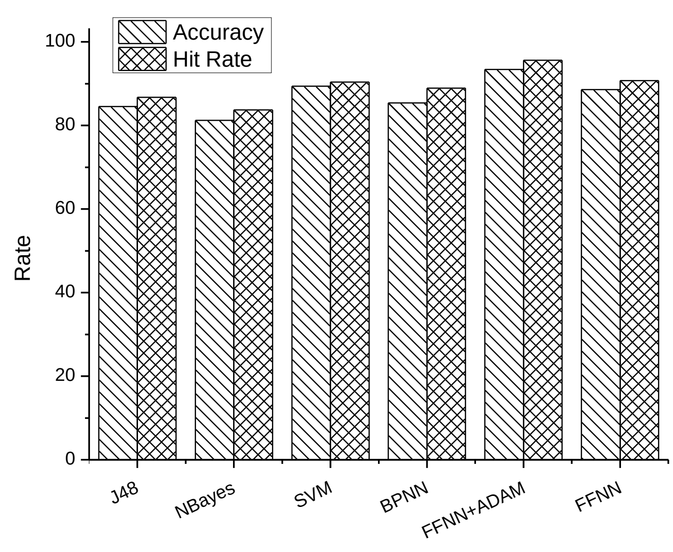

Fig. 2. Brainwave accuracy and hit rate among different classifiers.

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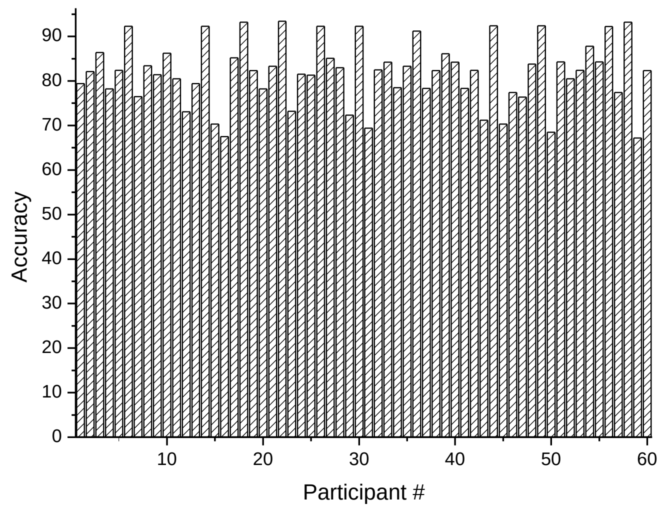

Fig. 3. Brainwave accuracy on different participants using FFNN+ADAM.

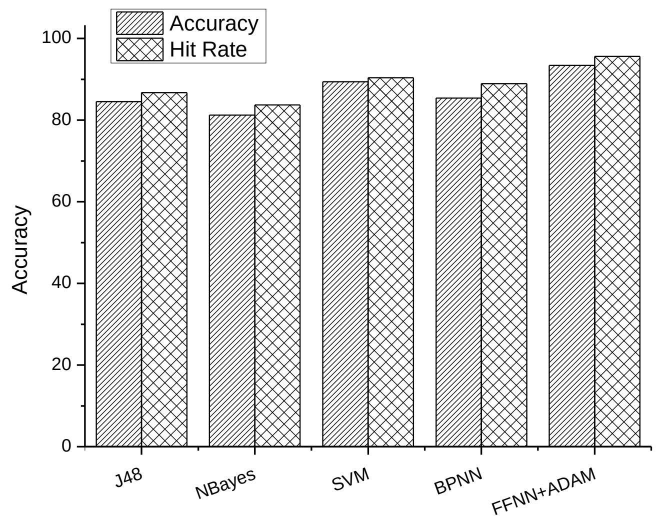

Fig. 4. Touch behavior accuracy and hit rate among different classifiers.

they face a similar scenario. This confirms the observations in previous studies [2], [37].

Touch behavior. The second layer of our system can verify touch behavior of users, we adopted the TMGuard scheme [29] to identify the behavioral deviations. TMGuard is a mechanism that can validate users' touch movement during pattern input. Intuitively, we consider the behavior patterns would be different under comfortable and uncomfortable conditions. Fig. 4 depicts the accuracy and hit rate regarding touch behavior. It is found that the accuracy and hit rate of each classifier could perform better than those in Fig. 2, indicating that the deviation in touch behavior is more easily to distinguish as compared with brainwave signals. Similarly, the hybrid classifier of FFNN+ADAM could reach a better rate with accuracy of 93.4% and hit rate of 95.6%, than other classifiers.

Fig. 5 shows the accuracy regarding each participant by considering both brainwave signals and touch behavior. It is visible that the accuracy could be improved by 7-9% for most participants. This validates the effectiveness of our two-layer structure, in which the use of touch behavior can help enhance

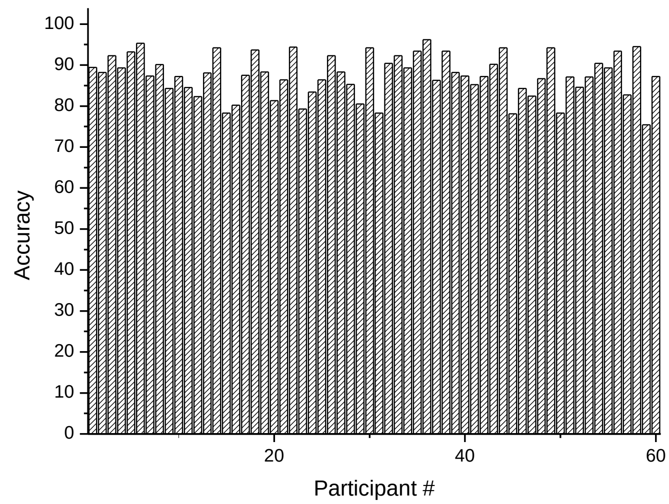

Fig. 5. The improved accuracy on different participants using FFNN+ADAM, based on both brainwaves and touch behavior.

the detection of user emotion.

V. Discussion

The results indicate the viability and effectiveness of our system, but there are still some challenges regarding emotion-aware IoMT applications and mechanisms.

- Under COVID-19, the data volumes transmitted in IoMT would become huge, and most data can be very sensitive (e.g., patient's home address, medical record, and biometric data). This requires deploying additional security mechanisms and privacy preserving techniques against cyber-attacks.
- Cost is an important factor for patients as well as healthcare professionals. As compared with speech, image and video recorder, brainwave headset is more expensive in practice. This is still an open challenge for IoMT applications, but with the increasing capability of smartphones, some integrated IoMT devices could be a solution.

To our best knowledge, brainwave-based emotion recognition has not been widely studied in healthcare. There are many potential improvements can be considered in our future work.

- *Algorithms.* In this work, we mainly devise a hybrid classifier and consider several supervised learning algorithms. In the literature, various algorithms have been studies like deep learning. In our future work, we plan to investigate how deep learning can contribute to our settings.
- *Touch behavior.* Different from touch-based authentication, this work mainly distinguishes the behavior deviation under comfortable and uncomfortable conditions. Our results indicate that the behavior deviation could be clearly visible between these two conditions. To further enhance the deviation detection, we plan to consider other touch behavior schemes and make a comparison.
- *Participants.* In this user study, we had 60 participants while more people with diverse background are expected to validate the results. It is still an open challenge to collect data in healthcare. Thus we plan to involve the people with other occupations in our future study.

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- *Modality data.* A modality can be considered as the classification of a single independent channel of either input or output between a computer and a human. More modality data relating to speech, image and video can be used to build a multi-modality data profile, with the purpose of enhancing the authentication performance. Fusion techniques are the promising solution to achieve this goal [22].
- *Fog computing.* Our system architecture reduces the computational burden using a cloud and edge computing environment. In practice, fog devices can also be used for the same purpose. Generally, fog computing and edge computing are the same thing. A small difference is that edge devices are closer to the sensor while the fog devices may be physically more distant from the sensor [26].
- *Evaluation metrics.* In this work, we mainly consider evaluating our system in terms of authentication accuracy, as it is very important for brainwave authentication. For real-world implementation, some other metrics could also be important such as latency, energy consumption and scalability, which can affect the system usability. How to make a balance between security (authentication) and usability is a challenge in this area. In our future work, we plan to investigate the scalability and usability issues by collaborating with a healthcare organization.
- *Attacks and threat.* Though EEG-based authentication can benefit people's daily lives, it may also pose some security issues especially under attacks. Chiu et al. [10] showcased a brainwave-based computer-screen unlock mechanism, and figured out a type of reaction spoofing attack where an attacker can imitate the mental reaction (either familiar or unfamiliar) of a legitimate user. To test the robustness of our system under attacks is one of our future work.
- *Multimodal system.* This work demonstrates an emotion-aware monitoring system that combines brainwave and touch behavior, while some other factors can be integrated for emotion recognition like speech and video [22]. In addition, other behavioral features can be considered, like walking patterns that are helpful to identify emergency conditions when users fall down. A multimodal system is desirable to provide better detection accuracy.

VI. Conclusion

With a number of connected medical devices, IoMT can sense, collect, transmit and analyze medical data, which can provide remote healthcare monitoring and timely symptom detection. Under the outbreak of pandemic like COVID-19, there is an increasing need to monitor and recognize human emotion, especially children, sensitive people and elderly for better emergency assistance.

In this work, we develop an emotion-aware healthcare monitoring system with the aim to complement existing emotion-aware IoMT applications and software. Our system adopts a two-layer structure, where the first layer can recognize emotions based on brainwaves (EEG) signals and the second layer can confirm the emergency scenario by analyzing user's touch behavior. We also devise a hybrid classifier of Feed-Forward Neural Network with First-Order Stochastic Optimization algorithm (ADAM). In our study with 60 participants, the results demonstrate the viability and the effectiveness of our system in distinguishing user' emotion under either comfortable or uncomfortable conditions. The emotion recognition of combining brainwaves and touch behavior can improve the accuracy by 7-9% on average than solely analyzing brainwaves.

The future work could include investigating the combination of other modality data, and comparing the performance of our hybrid algorithm with other similar algorithms. In our future work, we also consider exploring the latency and energy consumption caused by our approach.

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